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A NEW APPROACH FOR PERSON VERIFICATION SYSTEM BASED ON FINGER-KNUCKLE PRINT BIOMETRIC AND MLP NEURAL NETWORK

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ABSTRACT

Developing secure and effective access-control systems requires person-identification technologies that are reliable and convenient. This paper presents a new approach for the human identification system, which is based on the finger-knuckle print biometrics. The system uses image statistics and Two- Dimensional Discrete Walsh Hadamard Transform domain coefficients for the feature extraction. Principal component analysis is specifically used for the input dimensionality reduction of the feature vector. The Multi Layer Perceptron (MLP) Neural Network is recommended for precise and accurate recognition of a person. The performance of the proposed system is evaluated in terms of classification accuracy. The experimental results showed that the proposed person verification system achieved 100% accuracy on testing dataset.

KEYWORDS: Biometrics, Finger-Knuckle, Neural Network, Multi Layer Perceptron (MLP), Discrete Walsh Hadamard Transform (DWH), Principal Component Analysis (PCA)

1. INTRODUCTION

Biometrics refers to metric related to human characteristics, which is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance. The main purpose of person identification is to prevent multiple users from claiming a single identity. Traditional identification or security control includes token-based identification systems, such as a driver's license or passport, and knowledge-based identification systems, such as a password or personal identification number. Since biometric identifiers are unique to individuals, they are more reliable in verifying identity than token and knowledge-based methods.

The most common biometric systems are based on characteristics that are commonly used by humans for identification, such as fingerprint, iris, etc. However, many other human characteristics are also being examined as possible biometric cues for human recognition.

The finger-back surface also known as the dorsum or finger-knuckle can be very useful in person verification. The anatomy of our fingers permit them to bend forward and resist backward motion. This asymmetry results in a very limited number of creases and wrinkles on their palm-side. The image-pattern formed due to finger-knuckle bending is highly unique and thus makes this surface a distinctive biometric identifier. This paper suggests the finger Knuckle based person verification system, which is more convenient and user friendly as it relies on touchless imaging.

The rest of the paper is organized as follows: A review of related reported work is given in section 2. Section 3 describes database used in our work. Feature extraction methods are described in section 4. Section 5 presents brief

introduction of Artificial Neural Network and MLP. Section 6 provides the computer simulation and experimental results in order to demonstrate the suitability of our approach. Finally, Section 7 presents conclusion.

2. LITERATURE REVIEW

The image pattern formation from the finger-knuckle bending is highly unique and makes this surface a distinctive biometric identifier [Woodard and Flynn, 2005]. [Woodard and Flynn, 2005] were the first to use 3D finger surface feature in biometric systems. They used curvature based shape index to represent the fingers surface. But, their work did not provide a practical solution in establishing an efficient system using the outer fingers. Later, [Kumar and Ravikanth, 2007; Kumar and Ravikanth, 2009] suggested another approach to personal authentication using 2D finger-back surface imaging and finger geometry features. [Kumar and Zhou, 2009; Kumar and Zhou, 2009] used the robust line orientation code proposed in Jia et al. 2008 to extract the orientation of the finger-back surface images. [Ribaric and Fratric, 2005] presents a multimodal biometric identification system based on eigenfinger and eigenpalm features of the human hand. Apart from that, [Loris and Alessandra, 2009] reported multi-matcher biometric approach based on Parzen window classifiers, using knuckle-based features extracted from the middle finger and from the ring finger. [Kumar and KamYuen C., 2012] has detailed the usage of finger knuckle surface for online person identification. [Zhu Le-qing 2011] proposed the wavelet based approach for extracting the key features of Knuckle print and used SURF algorithm for the finger print recognition. [Shariatmadar Z. S et al. 2011] presents present a novel method for personal identification, which includes Gabor filter bank, combination of PCA and LDA algorithms and Euclidean distance measure. Recently [Usha, K. et al. 2014] suggested a novel finger knuckle print (FKP) recognition technique based on Haar-Wavelet Transform (HWT) and correlation classifier. Artificial Neural Network based approach is also proposed by some authors, [Islam, M. et al. 2012] proposed a hybrid feature extraction method based on Lempel-Ziv Feature Selection and Principal Component Analysis and an Artificial Neural Network based on Scaled Conjugate Gradient was used for the recognition. [Kale, K.V et al. 2013] reported on a approach combing Finger-knuckle and finger-nail features, where they also proposed the feed forward back propagation Neural Network for the classifier.

This paper presents similar Neural Network based approach for the person verification from finger-Knuckle images. Figure 1 shows the architecture of proposed automated ear biometrics system. The Multi Layer Perceptron (MLP) NN is used in the recognition stage. We employ image statistics and Two- Dimensional Discrete Walsh Hadamard Transform for the feature extraction. Input dimensionality reduction is obtained by using Principal component analysis (PCA) and the optimized MLP is suggested for the biometrics.

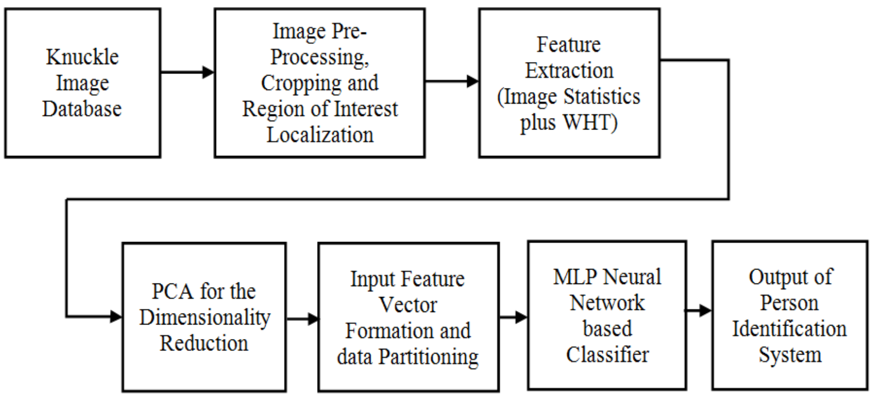

Figure 1: Architecture of Proposed System

3. FINGER-KNUCKLE IMAGE DATABASE

The Finger knuckle image database considered for this work is acquired from Indian Institute of Technology (IIT) Delhi. This image database is comprised of the images acquired from the students and staff at IIT Delhi, India. This database has been acquired using a digital camera. The currently available database is obtained from 158 users, and all the images are in bitmap (*.bmp) format. All the subjects in the database are in the age group varying from 16-55 years. This database of 790 images has been sequentially numbered for every user with an integer number. The resolution of these images is 80 × 100 pixels. The sample images from this database are reproduced in Figure 2.

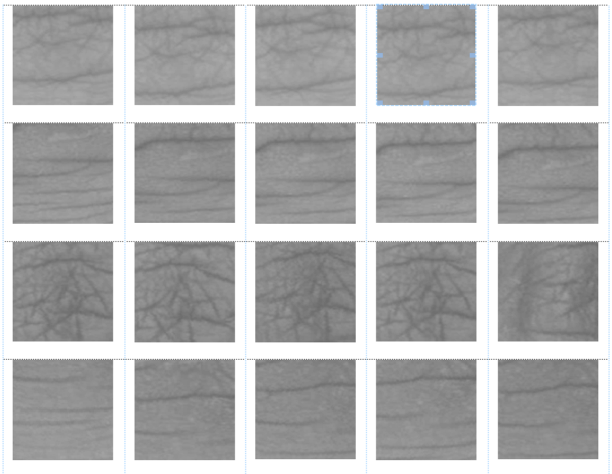

Figure 2: Sample Finger Knuckle Images

4. FEATURE EXTRACTION

The feature vector is formed after the pre-processing and region of interest localization of 2D finger knuckle images. Features are obtained with the help of image statistics and Two- Dimensional Discrete Walsh Hadamard Transform. The image statistics includes features such as average Standard Deviation (SD), Contrast, Correlation, Energy and Homogeneity. These features are explained as follows:

4.1. Image Statistics

Average: Average indicates two dimensional mean of gray image matrix.

Standard Deviation: Standard deviation of elements contained in image matrix. and is calculated by using formula:

$$SD = \left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^{1/2} \tag{1}$$

Entropy: Entropy is a statistical measure of randomness which may be used to characterize the texture of input image. It is defined as,

$$\text{Entropy} = -\sum \rho \log_2(\rho) \tag{2}$$

where, ρ denotes the histogram counts of an image. Image texture provides information about the spatial arrangement of color or intensities in an image or selected region of an image. Gray Level Co-occurrence Matrix (GLCM) indicates numerical features of a texture using spatial relations of similar gray tones. Numerical features calculated from

GLCM can be used to represent, compare and classify textures. This matrix shows how often a pixel with gray scale intensity (gray level) value *i* occurs horizontally adjacent to a pixel with the value *j*. After creating the GLCM of image, several statistics of image are obtained like Contrast, correlation, energy and homogeneity etc.

Contrast: It is defined as separation between the darkest and brightest area of an image. It measures the local variations in the gray level co-occurrence matrix.

$$Contrast = \sum_{i,j} |i-j|^2 p(i,j) \tag{3}$$

Correlation: It is a measure of how correlated a pixel is to its neighbor over the whole image.

Energy: Energy denoted the sum of squared elements in GLCM. It is also known as uniformity or the angular second moment.

Homogeneity: Homogeneity is a measure of texture of an image. It measures the closeness of the distribution of elements in the GLCM to the diagonal of GLCM.

4.2. Walsh-Hadamard Transform (WHT)

The Walsh-Hadamard Transform (WHT) is a suboptimal, non-sinusoidal, orthogonal transformation that decomposes a signal into a set of orthogonal, rectangular waveforms called Walsh functions. The transformation has no multipliers and is real because the amplitude of Walsh (or Hadamard) functions has only two values, +1 or -1. Fast algorithms for computing the WHT are similar to the Fast Fourier Transform (FFT) and its variants. The Walsh-Hadamard transform of a signal *x*, of size N=2n, is the matrix-vector product WHT_N.x, where

$$WHT_N = \otimes_{i=1}^{n} DFT_2 = \overbrace{DFT_2 \otimes \ldots \otimes DFT_2}^{n} \tag{4}$$

The matrix

$$DFT_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

is the 2-point DFT matrix, and ⊗ denotes the tensor or Kronecker product. The tensor product of two matrices is obtained by substituting each entry of the first matrix by that element multiplied by the second matrix. Thus, algorithms for computing the WHT can be derived using properties of the tensor product.

A recursive algorithm for the WHT is obtained from the factorization

$$WHT_{2^n} = (WHT_2 \otimes I_{2^{n-1}})(I_2 \otimes WHT_{2^{n-1}}) \tag{5}$$

This equation corresponds to the divide and conquer step in a recursive FFT. An iterative algorithm for computing the WHT is obtained from the factorization

$$WHT_{2^n} = \prod_{i=1}^{n} \left(I_{2^{i-1}} \otimes WHT_2 \otimes I_{2^{n-i}} \right) \tag{6}$$

which corresponds to an iterative FFT. More generally, let n = n_1 + --- + n_t, then

$$WHT_{2^n} = \prod_{i=1}^{t} \left(I_{2^{n_1+--+n_{i-1}}} \otimes WHT_{2^{n_{i+1}+--+n_t}} \right) \tag{7}$$

This equation encompasses both the iterative and recursive algorithm and provides a mechanism for exploring different breakdown strategies and combinations of recursion and iteration. Alternative algorithms are obtained through different sequences of the application of the above equation.

5. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks are the family of statistical learning algorithms which are inspired from biological neural networks. ANNs are generally defined as structures comprised of densely interconnected adaptive simple processing elements that can process massively parallel computations for data. Neural Networks can be trained to estimate or approximate functions that depend on a large number of inputs and are generally unknown. The Multi-Layer-Perceptron was first introduced by M. Minsky and S. Papert in 1969. The multilayer perceptron neural network has the features such as ability to learn and generalization, smaller training set requirements, fast operation, stability and ease of implementation. Therefore, it is most commonly used neural network architecture for the pattern recognition and classification.

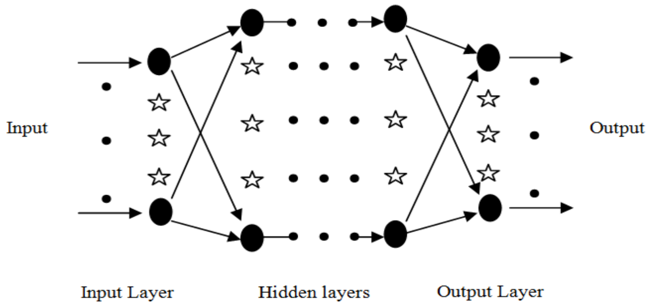

Figure 3: MLP-NN Structure

5.1 Multi Layer Perceptron Neural Network

Figure 3 depicts a simple structure of MLPNN. It contains input layer with the neurons representing the input variable, output layer with the neurons representing the dependent variables and the hidden layers containing the neurons which perform static mapping between input space and output space. It is a feed-forward network, where all signals flow in a single direction from the input to the output of the network. The output at a given instant is a function only of the input at that instant. In MLP, the neurons are linked together by the weighted connections. The optimal value for the weights is determined through the training process. There are numerous training algorithms used to train a MLPNN, but all are variants of error back propagation (BP) algorithm. [Haykin, 1994; Basheer and Hajmeer, 2000]. This algorithm propagates the error from the output neurons and computes the weight modifications for the neuron in the hidden layers. The input layer neurons only act as a buffer to distribute the input signal x_i to the hidden layer neurons. Each neuron j in the hidden layer sum its input signalsx_i, after multiplying them with the strengths of the respective connections $w_{ji}$from the input layer, and computes it output y_j, as the function of sum:

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{8}$$

Where function f is a sigmoid or hyperbolic tangent function. The backpropagation algorithm gives the change Δw_{ji}in the weight of connection between neuron i and j as:

$$\Delta w_{ji} = \eta \delta_j x_i \tag{9}$$

Where η denotes the leaning rate and δ_j is a factor depending upon whether neuron j is an output neuron or hidden neuron.

6. COMPUTER SIMULATION EXPERIMENTS AND RESULTS

For development of a Person verification System, a database maintained by I. I. T. Delhi has been used. Fifty five Knuckle print images corresponding to of eleven different persons are considered. We have five knuckle biometric images for every person. After image processing, cropping and Region of Interest localization, following features are extracted using MATLAB image processing toolbox.

- Seven features based on Image Statistics and
- 128 Coefficients of Two- Dimensional Discrete Walsh Hadamard Transform

Thus, each image is represented by 135 features. A knowledge base is created accordingly, that has 55 rows and 136 columns comprising of 135 columns as input and one column as the output. All inputs are numeric valued, whereas the output is symbolic representing name of the person. Moreover, in order to reduce the dimensionality of the input features, Principal Component Analysis is used. Figure 4 shows the graph for principal components versus Eigen values. Only 10 components are selected on the basis of the analysis, so that the dimensionality of the input space is reduced from 135 to only 10. Out of 55 exemplars, 11 exemplars are used for CV/Testing and remaining 44 instances are chosen for training the Multi Layer Perceptron Neural Network based classifier. As there are 10 PCs factors, which are computed by the PCA analysis of the original database; number of Processing Elements in the Input Layer of the MLP NN based classifier shall be 10. Similarly, as the task of Person identification from Knuckle-image biometrics is limited to only 11 different persons, the number of PEs in the output layer is 11. Simulation experiment is conducted to determine the number of PEs in the hidden layer and the number of hidden layers. Figure 5 depicts the variation in average minimum MSE with number of processing elements in hidden layer. From Figure 5 and Table 1, number of processing element in hidden layer is selected as 11.

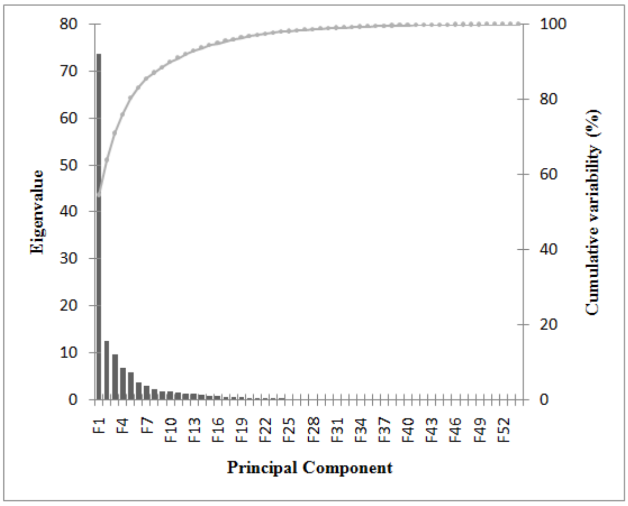

Figure 4: Eigen Values and Corresponding Factors Variability Plot

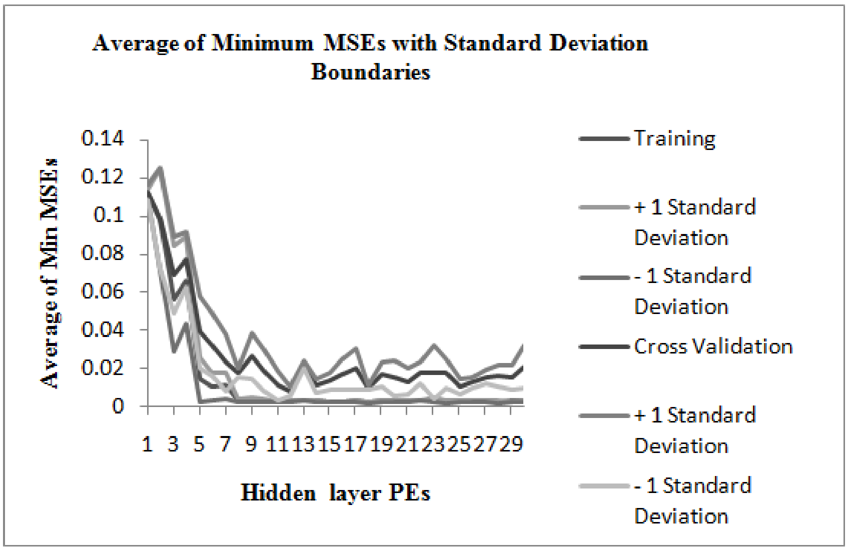

Figure 5: Variation of Average Minimum MSE with No. of PEs in Hidden Layer

Table 1: Minimum MSE and Processing Elements for the Hidden Layer

Best Networks	Training	Cross Validation
Hidden 1 PEs	28	11
Run	3	2
Epoch	1000	1000
Minimum MSE	0.001344595	0.005553569
Final MSE	0.001344595	0.005553569

The selected architecture of the MLP is (10-11-11). With this configuration of the MLP, the network is retrained three times on the Training dataset and tested on a different Cross-Validation (CV) dataset. Performance of the MLP-NN based classifier on training and testing/ CV dataset is shown in the Table 2 and Table3, respectively. It is noticed that all 11 persons from Person 1 to Person 11 are correctly identified with 100% Classification accuracy on the CV dataset. As 100 % classification accuracy is achieved from MLP (10-11-11) based classifier, the second hidden layer was not introduced as it would simply have increased the time as well as space complexity of the NN based classifier.

Table 2: Performance Parameters of MLP NN on Training Dataset

Performance	(Person11)	(Person10)	(Person9)	(Person8)	(Person7)
MSE	0.000633309	0.001558146	0.001207388	0.001746642	0.001391034
NMSE	0.007663036	0.018853563	0.014609395	0.021134369	0.016831506
Percent Correct	100	100	100	100	100

(Person6)	(Person5)	(Person4)	(Person3)	(Person2)	(Person1)
0.001450933	0.001457838	0.000708881	0.001145299	0.001964817	0.001120261
0.017556286	0.017639838	0.008577457	0.013858115	0.023774285	0.013555156
100	100	100	100	100	100

Table 3: Performance Parameters of MLP NN on CV/Testing Dataset

Performance	(Person11)	(Person10)	(Person9)	(Person8)	(Person7)
MSE	0.001506827	0.004015794	0.001881036	0.002353975	0.006871937
NMSE	0.018232612	0.048591113	0.02276054	0.028483096	0.083150441
Percent Correct	100	100	100	100	100

Table 3: Contd.,					
(Person6)	(Person5)	(Person4)	(Person3)	(Person2)	(Person1)
0.005944579	0.005591667	0.003670311	0.001492348	0.002113649	0.002267296
0.071929411	0.067659173	0.044410761	0.018057417	0.025575155	0.027434283
100	100	100	100	100	100

7. CONCLUSIONS

This paper has proposed a novel person identification system based on finger knuckle images and the artificial neural network. The image statistics and Two Dimensional Walsh Transform domain coefficients are used for forming the feature vector. In order to remove the redundant or irrelevant features and also reduce the burden of the classification system, PCA is presented and used to select the most significant features. We have employed the multilayer perceptron neural network for the verification purpose. MLP was retrained three times with different random initialization of connection weights and biases so as to ensure the true learning. The performance of multi layer perceptron is evaluated in terms of average classification accuracy. It is observed that MLP (10-11-11) with a single hidden layer has yielded the excellent performance. It found that MLP NN based classifier has 100% classification accuracy when tested on Testing/CV dataset, which truly justifies the efficacy of our person verification system.

List of Abbreviations

ANN	Artificial Neural Network
CV	Cross Validation
DFT	Discrete Fourier Transform
DWH	Walsh Hadamard Transform
IIT	Indian Institute of Technology
MLP	Multilayer Perceptron
MSE	Mean Square Error
NN	Neural Network
NMSE	Normalize Mean Square Error
PEs	Processing Elements
PC	Principal Components
PCA	Principal Component Analysis
SD	Standard Deviation

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